

Auto-scaling Web Applications in Clouds: A Taxonomy and Survey

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Web application providers have been migrating their applications to cloud data centers, attracted by the emerging cloud computing paradigm. One of the appealing features of cloud is elasticity. It allows cloud users to acquire or release computing resources on demand, which enables web application providers to auto-scale the resources provisioned to their applications under dynamic workload in order to minimize resource cost while satisfying Quality of Service (QoS) requirements. In this paper, we comprehensively analyze the challenges remain in auto-scaling web applications in clouds and review the developments in this field. We present a taxonomy of auto-scaling systems according to the identified challenges and key properties. We analyze the surveyed works and map them to the taxonomy to identify the weakness in this field. Moreover, based on the analysis, we propose new future directions.

CCS Concepts: **•Software and its engineering** → *Cloud computing*; **•Networks** → *Cloud computing*; **•Computer systems organization** → *Cloud computing*;

Additional Key Words and Phrases: Auto-scaling, web application, cloud computing

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1. INTRODUCTION

Cloud computing is the emerging paradigm for offering computing resources and applications as subscription-oriented services on a pay-as-you-go basis. one of its features, called elasticity, which allows users to dynamically acquire and release the right amount of computing resources according to their needs is continuously attracting web application providers to move their applications into clouds.

To efficiently utilizing elasticity of clouds, it is vital to automatically and timely provision and deprovision cloud resources, since over-provisioning leads to resource wastage and extra monetary cost, while under-provisioning causes performance degradation and violation of service level agreement (SLA). This mechanism of dynamically acquiring or releasing resources to meet QoS requirements is called auto-scaling.

However, designing and implementing an efficient general purpose auto-scaling system for web applications is a challenging task due to various factors, such as dynamic workload characteristics, diverse application resource requirements, and complex cloud resource and pricing models. In this paper, we aim to comprehensively analyze the challenges in the implementation of an auto-scaler in clouds and review the developments for researchers that are new to this field. We present a taxonomy regarding the various challenges and key properties of auto-scaling web applications. We

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compare the existing works and map them to the taxonomy to discuss their strength and weakness. Based on the analysis, we also propose promising future directions that can be pursued by researchers to improve the state-of-the-art.

Lorido-Botran et al. [Lorido-Botran et al. 2014] have already written a survey about this topic. However, their focus is on resource estimation techniques while omitting other important challenges such as oscillation mitigation, and resource planning. Different from them, our work provides comprehensive discussions about all the major challenges in the topic and it also introduces new developments after their work.

The rest of the paper is organized as follows. In Section 2, we describe our definition of the auto-scaling problem for web applications and list its major challenges that need to be addressed when trying to implement one. After that, we present a taxonomy regarding the existing auto-scaling systems. From Section 4 to Section 12, we introduce and compare how the existing auto-scaling systems tackle the listed challenges. After that, in Section 13, we discuss the gaps of the current solutions and present some promising future research directions. Finally, we summarize the findings and conclude the paper.

2. PROBLEM DEFINITION AND CHALLENGES

In a single cloud, the auto-scaling problem for web applications can be defined as how to autonomously and dynamically provision and deprovision a set of resources to cater for fluctuant application workloads so that the resource cost is minimized and application service level agreements (SLAs) or service level objectives (SLOs) are satisfied. Figure 1 illustrates typical auto-scaling scenarios. In Figure 1(a), due to increase in requests, the available resources are in congestion, and thus, the auto-scaler decides to provision certain resources respectively to each application component. Adversely, in Figure 1(b), the auto-scaler deprovisions some resources from each component when the amount of requests has decreased.

This problem is a classic automatic control problem, which demands a system that dynamically tunes the type of resources and the number of resources allocated so as to reach certain performance goals, reflected as the SLA. Specifically, it is commonly abstracted as a MAPE control loop, Monitoring, Analysis, Planning, and Execution [Kephart and Chess 2003]. The control cycle continuously repeats itself as the time passes.

The major challenges of the problem lie in each phase of the loop as shown in Figure 2. We briefly explain each phase and summarize the individual challenges faced by auto-scaler designers in the following paragraphs.

Monitoring. The system needs to monitor some performance indicators to determine whether scaling operations are needed and how they should be performed.

- Performance indicators: the selection of the right performance indicators are vital to the success of the auto-scaler. The decision is often affected by many factors, such as application characteristics, monitoring cost, SLA, and the control algorithm itself.
- Monitoring interval: the monitoring interval determines the sensitivity of the auto-scaler. However, very short monitoring intervals result in high monitoring cost, both in terms of computing resources and financial cost, and it is likely to cause oscillations in the system. Therefore, it is important to tune this parameter to achieve balanced system performance.

Analysis. During the analysis phase, the system determines whether it is necessary to perform scaling actions based on the monitored information.

- Scaling timing: the system firstly needs to decide when to perform the scaling actions. It can either proactively provision/deprovision resources ahead of the workload

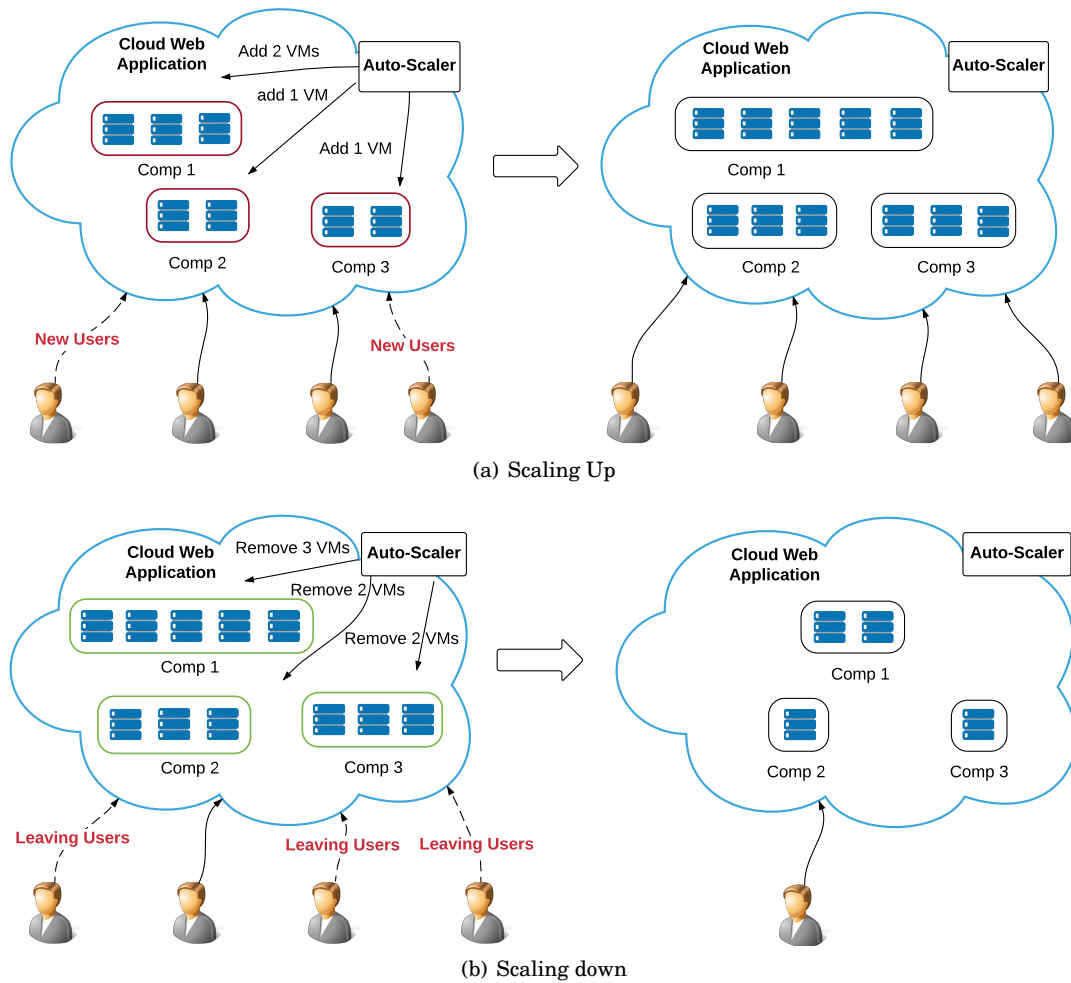


Fig. 1: Typical auto-scaling scenarios — right sizing of resources

changes if they are predictable, since the provision/deprovision process takes considerable time, or it can perform actions reactively when workload change actually happens.

- Workload prediction: if the system chooses to proactively scale the application, how to accurately predict the future workload is a challenging task.
- Adaptivity to changes: sometimes the workload and the application may undergo substantial changes. The auto-scaler should be aware of the changes and timely adapt its model and settings for the new situation.
- Oscillation mitigation: scaling oscillation means the system frequently performs contradictory actions within a short period of time (i.e., acquiring resources and then releasing resources or vice versa). It should be prevented as it results in resource wastage and more SLA violations.

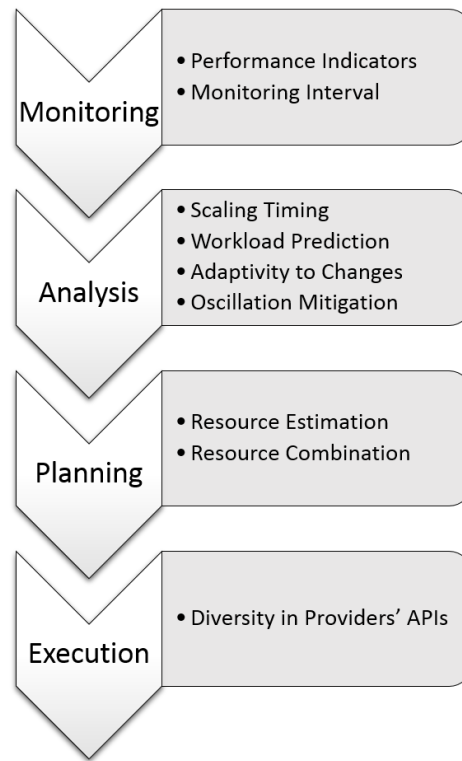


Fig. 2: The challenges of auto-scaling web applications in each phase of the MAPE loop

Planning. The planning phase estimates how many resources in total should be provisioned/deprovisioned in the coming scaling action. It should also optimize the composition of resources to minimize financial cost.

- Resource estimation: the planning phase should be able to estimate how many resources are just enough to handle the current or incoming workload. This is a difficult task as the system has to figure out this information quickly without being able to actually execute the scaling plan to observe the real application performance, and it has to take the specific application deployment model into account in this process.
- Resource combination: to provision resources, the system can resort to both vertical scaling and horizontal scaling. If horizontal scaling is employed, as the cloud providers offer various types of VMs, the system should determine which of them are picked for hosting the application. Another important factor is the pricing model of the cloud resources. Whether to utilize on demand resources, reserved resources, or rebated resources greatly affects the total resource cost. All these factors form a huge optimization space, which is challenging to solve efficiently in short time.

Execution. The execution phase is responsible for actually executing the scaling plan to provision/deprovision the resources. It is straightforward and can be implemented by calling cloud providers' APIs. However, from engineering point of view, being able to support APIs of different providers is a challenging task.

If the application is supposed to be deployed in multiple data centers, it is also important to identify which data center is most cost-efficient to serve the requests from

certain groups of users without violating SLAs. Therefore, in addition to provision just enough amount of resources during runtime, the auto-scaling problem becomes a mixed problem of data center selection, geographical load balancing, and resource provision in multi-cloud scenario. The auto-scaler should dynamically direct users from certain areas to specific data centers, and ensure enough resources are provisioned in each of the involving data centers to handle the incoming requests. To minimize cost in this scenario, considering all available choices in these tasks, it generally requires solving a NP-hard problem to generate the provision plan.

3. TAXONOMY

Figure 3 illustrates our proposed taxonomy for auto-scaling web applications in clouds. The taxonomy classifies the existing works based on the identified challenges in each of the MAPE phase in Section 2 and their targeted environment. Particularly, the taxonomy covers the following aspects in auto-scaling:

- Application Architecture: the architecture of the web application that the auto-scaling system is managing.
- Session Stickiness: whether the auto-scaling system supports sticky session.
- Adaptivity: whether and how the auto-scaling system adjusts itself to adapt to changes of workload and application.
- Scaling Indicators: what metrics are monitored and measured to make scaling decisions.
- Resource Estimation: how the auto-scaling system estimates the amount of resources needed for specific type and amount of workload.
- Oscillation Mitigation: how the auto-scaling system reduces the chance of provision oscillation.
- Scaling Timing: whether the auto-scaling system supports proactively scaling the application and how it predicts future workload.
- Scaling Methods: how the auto-scaling system decides using what methods to provision resources and what combination of resources are provisioned to the application.
- Environment: whether the auto-scaling system works in a single or multi-cloud environment.

An existing system generally spans across different subcategories and are discussed in each of them (i.e., the auto-scaling system is built in a single cloud environment for multi-tier applications, and employs proactive scaling with machine learning resource estimation techniques). Note that this taxonomy is based on features and thus does not reflect the relative performance of the proposed systems. Actually, because the surveyed systems target diverse workload patterns, application architectures, and pricing models, there is no single answer to the question that which approach generally performs the best.

In the following Sections (from Section 4 to Section 12), we introduce and compare the existing auto-scaling systems according to this taxonomy.

4. APPLICATION ARCHITECTURES

There are three types of web application architectures mentioned in the literature: namely single tier, multi-tier, and service-oriented architecture.

4.1. Single Tier/Single Service

A tier represents the software function implemented and packaged as the minimum interactive module in a layered software stack. In production deployment, a server usually exclusively host a single software tier, and within a tier, a load balancer is used to balance and dispatch load among the participating instances of the tier cluster. Sin-

gle tier architecture by definition is the architecture in which application is composed of only one tier. Relatively, the architecture with multiple connected software tiers is called multi-tier architecture. Instead of calling single tier as an application architecture, it is more accurate to think it as the smallest granularity that can be possibly managed by an auto-scaler, since hardly any web application is composed of only one tier.

Nowadays web applications are becoming more and more complicated and deviate from the traditional multi-tier architecture. In those cases, the basic scaling component is often referred as a service. The majority of the existing auto-scaling systems separately manage each single tier or service within an application instead of considering the application as a whole. The merits of the method are its simplicity and generality. However, it often results in global suboptimal resource provision as it requires to divide the SLA requirements of the overall application into sub-requirements of each tier or service, which is often a difficult and subjective task.

4.2. Multi-tier

Multi-tier applications as introduced in the previous Section are applications composed of sequentially connected tiers. At each tier, the request either relies on the downstream tier to complete its processing or it is returned to the upstream tier and finally to the user.

A common architecture of this type usually consists three tiers: one frontend tier, one application logic tier, and one database tier. The database tier is often considered dynamically unscalable and ignored by the auto-scaling systems.

There are many works that have targeted multi-tier applications. Some of them employ the divide and conquer approach that breaks overall SLA into SLA of each tier, such as the works done by Urgaonkar et al. [Urgaonkar et al. 2008], Singh et al. [Singh et al. 2010], Iqbal et al. [Iqbal et al. 2011], Malkowski et al. [Malkowski et al. 2011], Upendra et al. [Upendra et al. 2011], and Gergin et al. [Gergin et al. 2014]. Others consider the SLA of the whole application and provision the resources to each tier holistically. This strategy requires more efforts in modelling and estimating resource consumptions using complex queueing networks and machine learning techniques as discussed in Section 8, and the resulted auto-scalers are only applicable to multi-tier applications. Important works of this kind include systems proposed by Zhang et al. [Zhang et al. 2007], Jung et al. [Jung et al. 2008], Padala et al. [Padala et al. 2009], Lama and Zhou [Lama and Zhou 2009; Lama and Zhou 2010], Han et al. [Han et al. 2014], and Kaur and Chana [Kaur and Chana 2014].

4.3. Service-oriented Architecture

Service-oriented architecture (SOA) has now become the dominant paradigm for large web applications, such as Amazon e-commerce website, and Facebook. In this kind of architecture, applications are composed of standalone services that interact with each other through pre-defined APIs. More importantly, the services are not necessarily connected sequentially as in multi-tier applications. SOA applications are commonly abstracted as directed graphs with each nodes representing services and directed edges as their interactions.

Due to its complexity, it is difficult to manage resource provision of all the composing services holistically. Therefore, industry and most works employ the divide and conquer approach. Differently, Jiang et al. [Jiang et al. 2010] proposed a system that is able to guarantee the SLA of the whole SOA application. It is based on a bottom-up approach with each service estimating its performance after having one instance added or removed. Then it determines that scaling which service can bring the greatest benefit in terms of response time.

5. SESSION STICKNESS

Session is the concept of a series interactions between a client and the application. Between each operation, the client halts to read the feedback of the last operation given by the application and then issues the next move. To ensure seamless experience, it is necessary to keep the intermediate statuses of the clients during their sessions, otherwise, the operations conducted by the clients will be lost and they have to repeat the previous operations to proceed. Taking a social network application as an example, a session can involve the following operations: the client first accesses the home page and then logs into the application; after that, he performs several actions such as viewing his and his friends' timeline, uploading photos, and updating his status, before he quits the application.

This session based access pattern has caused issues on efficiently utilizing elastic resources in cloud. This is because the stateful nature of session forces the user to be connected to the same server each time he submits a request within the session, if the session data is stored in the server. Such sessions are called sticky sessions. They limit the ability of the auto-scaler to terminate under-utilized instances when there are still unfinished sessions handled by them. Therefore, it is generally considered a prerequisite to transform stateful servers into stateless servers before they can be managed by an auto-scaler.

There are multiple ways to achieve this and a complete introduction of them is out of the scope of this paper. The most adopted approach is to move the session data out of the web servers and store them either at user side or in a shared memcache cluster.

Though most auto-scaling systems require the scaling cluster to be stateless, there do exist exception systems that can handle stateful instances. Chieu et al. [Chieu et al. 2011] proposed an auto-scaling system based on the number of active sessions in each server. They restricted the server only can be terminated when there is no active session in it. Grozev and Buyya [Grozev and Buyya 2014b] proposed a better system by integrating a similar auto-scaling system with a load balancing algorithm that consolidates sessions within as few instances as possible.

6. ADAPTIVITY

Auto-scaling systems generally fall in the realm of control systems. As stated in the introduction, they involve tuning the resources provisioned to the application in order to reach the target application performance. One major issue coupled with the design of a control system is its adaptivity to changes. As in dynamic production environment, workload characteristic, and even the application itself can change at any moment. Therefore, adaptivity is important to auto-scaling systems. Based on the level of adaptivity, we classify the existing works into three categories.

6.1. Non-adaptive

In the non-adaptive systems, the control model is predefined and the systems make decisions purely based on the current input. Examples are the rule-based systems employed by the industry, such as Amazon Auto-Scaling service [Amazon 2016]. They require the user to define a set of scaling up and scaling down conditions and actions offline. During production time, the auto-scaler makes scaling decisions only when the conditions are met. They do not allow automatic adjustment of the settings during production. When using this kind of systems, the users often need to spend a lot of efforts in offline testing to find the suitable settings.

6.2. Self-adaptive

Self-adaptive auto-scaling systems are superior than their non-adaptive counterparts. Though the core control models in them are fixed as well, they are capable of autonomously tune themselves according to the real-time observed quality of the control actions. In this way, the designer only needs to determine the core control model, such as whether it is linear or quadratic, and the system will adjust and evolve itself to meet the target performance. This feature can be implemented through extending the pre-existing self-adaptive control frameworks in control theory such as Kamra et al. [Kamra et al. 2004], Kalyvianaki et al. [Kalyvianaki et al. 2009], and Grimaldi et al. [Grimaldi et al. 2015]'s work. Self-adaptivity can also be realized by dynamic measurement or correction of parameters in analytical models and machine learning approaches, such as reinforcement learning and regression. The detailed explanations of them are given in Section 8.

The benefit of introducing self-adaptivity is that it greatly reduces the amount of offline preparation required to utilize an auto-scaler. Furthermore, once substantial changes are detected, self-adaptive systems can autonomously abort the current model and retrain itself, thus, mitigating the maintenance effort as well. Their major drawback is that usually it takes time for them to converge to a good model and the application will suffer from bad performance during the early stage of training.

6.3. Self-adaptive Switching

Beyond utilizing a single self-adaptive module, some systems have employed a more adaptive framework, which we call self-adaptive switching. In these systems, they parallel connect multiple non-adaptive or self-adaptive controllers and actively switch control between controllers based on their observed performance on the application. The included self-adaptive controllers continuously tune themselves in parallel. However, at each moment, only the selected best controller is able to provision resources. Patikirikoralala et al. [Patikirikoralala et al. 2011] employed this approach and Ali-Eldin et al. [Ali-Eldin et al. 2013] proposed a self-adaptive switching system based on classification of the application workload characteristics, i.e., their periodicity and the burstiness.

7. SCALING INDICATORS

The actions of auto-scaling systems are based on performance indicators of the application obtained through the monitoring phase. These indicators are produced and monitored by different levels of the infrastructure hierarchy from low level metrics at the physical/hypervisor level to high level metrics at the application level.

7.1. Low Level Metrics

Low level metrics in the context of the survey mean server information monitored at the physical server/virtual machine layer by hypervisors, such as utilization of CPU, memory, and network resources, memory swap, and cache miss rate. These information can be obtained through monitoring platform of the cloud provider or from monitoring tools for operating systems. However, it is a non-trivial task to accurately infer the observed application performance merely according to the low-level metrics, and therefore, makes it a difficult task to make sure that the SLA can be met faithfully with the available resources.

It is possible to design an auto-scaler solely based on low level performance indicators. The simplest solution is to use the utilization of CPU and other physical resources as indicators and scale up and scale down resources to maintain the overall utilization

within an defined upper and lower bound. This approach is widely adopted by industry systems.

7.2. High Level Metrics

High level metrics are performance indicators observed at the application layer. Those useful to auto-scaling include resource rate, average response time, session creation rate, throughput, service time, and request mix.

Some of the metrics, like request rate, average response time, throughput, and session creation rate, are easy to measure. These metrics alone enables operation of an auto-scaler. The easiest method to construct one is to replace utilization metrics in the simple auto-scaling system mentioned in the previous section with any of such high-level metric. However, the system like this is not able to accurately estimate the amount of resources needed and often over or under provision resources.

To estimate the amount of resources, some approaches require to obtain the information about request service time and request mix [Zhang et al. 2007; Singh et al. 2010; Kaur and Chana 2014]. These metrics are not straightforward to measure.

Service time is the time the server actually spent on processing the request, which is widely used in the queueing models to approximate the average response time or sojourn time. Except for a few works [Gergin et al. 2014; Han et al. 2014] that assume this metric as known a priori, to accurately measure it, either offline profiling [Prodan and Nae 2009] or support from the application [Aniello et al. 2014] is required. Therefore, instead of directly probing it, some works use other approaches to approximate it. Kaur and Chana [Kaur and Chana 2014] mentioned the use of past server logs to infer the mean service time. Gandhi et al. [Gandhi et al. 2014a] employed Kalman filters to estimate service time during runtime. Zhang et al. [Zhang et al. 2007] used a regression method to make the approximation. Jiang et al. [Jiang et al. 2011] resorted to profile each server when it is first online using a small workload without concurrency and then estimating service time through queueing theory. In another work, Jiang et al. [Jiang et al. 2010] utilized a feedback control loop to adjust the estimation of service time at runtime.

Request mix is hard to measure because understanding of the application is essential to distinguish different types of requests. Designing a mechanism to accurately classify different types of requests from outside of the application itself is an interesting and challenging problem to be explored.

7.3. Hybrid Metrics

For some systems, both high level and low level metrics are monitored. A common combination is to observe request rate, response time, and utilization of resources. Some systems [Prodan and Nae 2009; Gandhi et al. 2014a] monitor them because the queueing models employed for resource estimation require them as input. Some [Jing et al. 2007; Padala et al. 2009; Dutta et al. 2012; Yazdanov and Fetzer 2013; Fernandez et al. 2014] uses these hybrid metrics to dynamically build a model relating specific application performance to physical resource usage through online profiling, statistical, and machine learning approaches, thus increasing the accuracy of resource estimation without constructing complex analytical models. Another important reason to monitor request rate along with low level metrics is to conduct future workload prediction [Roy et al. 2011; Dutta et al. 2012].

Besides low level and high level metrics from the system, other factors outside the system may also play an important role. For example, Frey et al. [Frey et al. 2014] in their fuzzy-based system utilizes other related data, such as weather, and political events to predict workload intensity.

8. RESOURCE ESTIMATION

Resource estimation lies in the core of auto-scaling as it determines the efficiency of resource provisioning. It aims to identify the minimum amount of computing resources required to process the workload so as to determine whether and how to perform scaling operations. Accurate resource estimation allows the auto-scaler to quickly converge to the optimal resource provision. While estimation errors either result in insufficient provision, which leads to inevitable delay of the provision process and increased SLA violations, or resource wastage that incurs more cost.

Various attempts have been made to develop resource estimation models from rudimentary simple approaches to approaches with sophisticated models. We categorize them into six groups, namely rule-based, fuzzy inference, application profiling, analytical modelling, machine learning, and hybrid approaches. In the following subsections, we explain and compare the existing approaches in each group.

8.1. Rule-based Approaches

Rule-based approaches are widely adopted by industry auto-scalers, such as Amazon Auto-Scaling Service [Amazon 2016]. Its kernel is a set of predefined rules consisting of triggering conditions and corresponding actions, such as “If CPU utilization reaches 70%, add 2 instances”, and “If CPU utilization decreases below 40%, remove 1 instance”. As stated in Section 7, users can use any metrics, low-level or high level, to define the triggering conditions, and the control target of the auto-scaling system is usually to maintain the concerned metrics within the predefined upper and lower threshold. Theoretically, the basic rule-based system involves no accurate resource estimation, only empirical guessing hardcoded in the action part of the rule as adding or removing certain amount or percentages of instances. As the simplest version of auto-scaling, it commonly serves as benchmark for comparison and is used as the basic scaling framework for works that focus on other aspects of auto-scaling, such as Dawoud et al.’s work [Dawoud et al. 2012] which aims to compare vertical scaling and horizontal scaling, and Rui et al.’s work [Rui et al. 2012] which considers all possible scaling methods, or prototyping works, like the one carried out by Iqbal et al. [Iqbal et al. 2009].

Though simple rule-based auto-scaler is easy to implement, it has two major drawbacks. The first is that it requires understanding of the application characteristics and expert knowledge to determine the thresholds and proper actions. Al-Haidari et al. [Al-Haidari et al. 2013] conducted a study to show that these parameters significantly affect its performance. The second is that it cannot adapt itself when dynamic changes occur to workload and application.

Hardcoded number of instances to scale up and scale down, called step sizes, would become inappropriate when the workload changes dramatically. For example, if at start the application is provisioned by 4 instances, adding 1 instance will boost 25% of the capability. After a while, the cluster has increased to 10 instances due to workload surge, adding one instance in this case only increases 10% of capacity. Improvements are made to the basic model using adaptive step sizes. Netto et al. [Netto et al. 2014] proposed an approach that decides the step size holistically at runtime based on upper threshold, lower threshold, and the current system utilization. It first deduces the upper and lower bounds respectively for step sizes of scaling up and scaling down operations to prevent oscillation and then scale the step sizes using a fixed parameter representing the aggressiveness of the system determined by user. They reported the adaptive strategy performed best for bursty and peaky workload but lead to limited improvements for other types of workloads. Cunha et al. [Cunha et al. 2014] employed

a similar approach. However, in their approach, the aggressiveness parameter is also dynamically tunable according to QoS requirements.

In addition to the step size, fixed thresholds also could cause inefficient resource utilization. For instance, the thresholds of 70% and 40% may be suitable to small number of instances but are inefficient for large clusters as single instance has very small impact on the overall utilization and a lot of instances actually can be removed before the overall utilization reaching the 40% lower bound. The common solution to mitigate this problem is also to make the thresholds dynamic. Lim et al. [Lim et al. 2009; Lim et al. 2010] used this approach.

Another important variation of the simple rule-based approach is proposed by RightScale [RightScale 2016]. Its core idea is to let each instance decide whether to shrink or expand the cluster according to predefined rules and then utilize a majority voting approach to make the final decision. Calcavecchia et al. [Calcavecchia et al. 2012] also proposed a decentralized rule-based system. In their system, instances are connected as a P2P network. Each instance contacts its neighbours for their statuses and decides whether to remove itself or start a new instance in a certain probability derived from their statuses.

8.2. Fuzzy Inference

Fuzzy-based auto-scalers can be considered as a kind of advanced rule-based systems as they rely on fuzzy inference, the core of which is a set of pre-defined If-Else rules, to make provision decisions. The major advantage of fuzzy inference compared to simple rule-based approaches is that it allows to use linguistic terms like “high, medium, low”, instead of accurate numbers to define the conditions and actions. This makes it easier for human beings to effectively represent a priori knowledge (human expertise) about the system. Fuzzy inference works as follows: the inputs are first fuzzified using defined membership functions; then the fuzzified inputs are used to trigger the action parts in all the rules in parallel; the results of the rules are then combined and finally defuzzified as the output for control decisions. Representative systems of this kind include the one proposed by Frey et al. [Frey et al. 2014] and the work conducted by Lama and Zhou [Lama and Zhou 2009]. Due to the complexity of manually designing the rule set and possible changes may happen during runtime, fuzzy-based auto-scalers are commonly coupled with machine learning techniques to automatically and dynamically learn the rule set [Jing et al. 2007; Jamshidi et al. 2016; Lama and Zhou 2010]. Their details are introduced in Section 8.6.

8.3. Application Profiling

We define profiling as a process to test the saturating point of resources when running the specific application using synthetic workload or recorded real workload. Application profiling is the simplest way to accurately acquire the knowledge of how many resources are just enough to concurrently handle the given amount of workload. To profile an application, testing needs to be conducted either offline or on the fly.

Offline profiling is able to produce the complete spectrum of resource consumption under different levels of workload. With the obtained model, the auto-scaler can more precisely supervise the resource provisioning process. Upendra et al. [Upendra et al. 2011], Gandhi et al. [Gandhi et al. 2012], Fernandez et al. [Fernandez et al. 2014], and Qu et al. [Qu et al. 2016] employed this approach. The drawback of this approach is that the profiling needs to be reconducted manually every time the application is updated.

To overcome this issue, profiling can be carried out online. However, the online environment prohibits the auto-scaler to fine-grainedly profile the application as the VM should be put into service as soon as possible to cater the increasing workload. Vasić

et al. [Vasić et al. 2012] proposed a system that first profiles the application, then clusters the application signatures to workload classes (number of machines needed). When changes happen to the application, the profiled new application characteristics are fed into the trained decision tree to realize quick resource provisioning by finding the closest resource allocation plan stored before. Nguyen et al. [Nguyen et al. 2013] relied on online profiling to derive a resource estimation model for each application tier. When profiling each tier, other tiers are provisioned with ample resources. In this way, one by one, models for all the tiers are obtained. Jiang et al. [Jiang et al. 2011] proposed a quick online profiling technique for multi-tier applications by studying the correlation of resource requirements that different tiers pose on the same type of VM and the profile of a specific tier on that type of VM. This approach allows them to roughly deduct the performance of the VM on each tier without actually running each tier on it. Thus the newly acquired VM can be put into service in relatively quicker speed.

8.4. Analytical Modelling

Analytical modelling is a process of constructing mathematical models based on theory and analysis. For resource estimation problems in auto-scaling, dominant models are built upon queueing theory.

In the generalized form, a queue can be represented as $A/S/C$, where A is the distribution of time interval between arrivals to the queue, S is the distribution of time required to process the job, and C stands for the number of servers. Common choices for A in the existing works are M (Markov) which means that arrivals follow the Poisson process, and G (General) which stands the inter-arrival time has a general distribution. For S , the prominent alternatives are M (Markov) which represents exponentially distributed service time, D (Deterministic) which means the service time is fixed, and G (General) which stands the service time has a general distribution. Detailed introduction of different types of queues is out of the scope of this paper. Interested users can refer to the book [Gnedenko and Kovalenko 1989].

For a single application, tier, or service, if the underlying servers are homogeneous, it is more convenient to abstract the whole application/tier/service as a single queue with one server. Kamra et al. [Kamra et al. 2004], Villela et al. [Villela et al. 2007], Gandhi et al. [Gandhi et al. 2014a; Gandhi et al. 2014b], and Gergin et al. [Gergin et al. 2014] employed this method. Some described the cluster using a queue with multiple servers, like Ali-Eldin et al. [Ali-Eldin et al. 2012], Jiang et al. [Jiang et al. 2013], Aniello et al. [Aniello et al. 2014], and Han et al. [Han et al. 2014]. Other works modeled each server as a separate queue, such as the ones proposed by Doyle et al. [Doyle et al. 2003], Urgaonkar et al. [Urgaonkar et al. 2008], Roy et al. [Roy et al. 2011], Ghanbari et al. [Ghanbari et al. 2012], Kaur and Chana [Kaur and Chana 2014], Spinner et al. [Spinner et al. 2014], and Jiang et al. [Jiang et al. 2010]. A hybrid model is proposed by Be et al. [Bi et al. 2010], in which the first tier is modelled as a $M/M/c$ queue while other tiers are modelled as $M/M/1$ queues. Different from the traditional queueing theory, Salah et al. [Salah et al. 2015] used an embedded Markov chain method to model the queueing system.

When the application involves multiple tiers or is composed of multiple services, single layer queueing models are insufficient, instead a network of queues is needed to describe the components and their relations. These models are known as queueing networks. As introduced in Section 4.2 and 4.3, to decide the amount of resources in each component, there are two strategies. One is to divide the SLA into separate time portions and distribute them to each component. By this method, the queueing model of each component can be easily solved. However, it usually results in suboptimal solutions globally. Another method is to holistically provision resources to all the

components to satisfy the SLA. Such method is more challenging as it is difficult and computationally heavy to find the optimal resource provision plan regarding a complicated queueing network model.

To tackle the challenge, a number of models and methods have been proposed. Villela et al. [Villela et al. 2007] described the model as an optimization problem and used three different approximations to simplify the problem. Bi et al. [Bi et al. 2010] as well employed an optimization approach. Roy et al. [Roy et al. 2011] and Zhang et al. [Zhang et al. 2007] utilized MVA (Mean Value Analysis), a widely-adopted technique for computing expected queue lengths, waiting time at queueing nodes, and throughput in equilibrium for a closed queueing network, to anticipate the utilization at each tier under specific provision. Han et al. [Han et al. 2014] adopted a greedy approach that continuously adds/removes one server to the most/least utilized tier until the estimated capacity is just enough to serve the current load.

As mentioned in Section 7.2, some of the parameters in the queueing models are hard to measure directly, like service time. Therefore, the proposed auto-scalers should properly handle this issue as well. The detailed techniques have already been introduced in Section 7.2.

8.5. Machine Learning

Machine learning techniques in resource estimation are applied to dynamically construct the model of resource consumption under specific amount of workload (online learning). In this way, different applications can utilize the auto-scalers without customized settings and preparations. They are also more robust to changes during production as the learning algorithm can self-adaptively adjust the model on the fly regarding any notable events. To realize self-adaptive evolution, the online machine learning algorithms are often implemented as feedback controllers. Though offline learning can also be used to fulfill the task, it inevitably involves human intervention and thus loses the benefit of using machine learning. For works that use offline learning — if there exists any, we classify them into the application profiling category.

Despite of easiness of usage and flexibility, machine learning approaches do suffer a major drawback. It takes time for them to converge to a stable model and thus causes the auto-scaler to perform poorly during the active learning period. Certainly, the application performance is affected in this process. Furthermore, the time taken to converge is difficult to predict and varies case by case and algorithm by algorithm.

Online learning used by existing auto-scalers can be divided into two types: reinforcement learning, and regression.

8.5.1. Reinforcement Learning. Reinforcement learning aims to let the software system learn how to react adaptively in a certain environment to maximize its gain or reward. It is suitable to tackle automatic control problems like auto-scaling [Tesauro 2005; Zhu and Agrawal 2012; Dutreilh et al. 2010; Dutreilh et al. 2011; Li and Venugopal 2011; Barrett et al. 2013; Bu et al. 2013; Yazdanov and Fetzer 2013; Fallah et al. 2015; Iqbal et al. 2015]. For the auto-scaling problem, the learning algorithm's target is to generate a table specifying the best provision or deprovision action under each state. The learning process is similar to a trial-and-error approach. The learning algorithm chooses a certain operation, and then observes the result. If the result is positive, the system will be more likely to take the same action next time when it faces a similar situation.

The most used reinforcement learning algorithm in the auto-scaling literature is Q-learning. A detailed description of the Q-learning algorithm and their variations in auto-scaling can be found in Section 5.2 of the survey by Llorido-Botran et al. [Llorido-Botran et al. 2014].

8.5.2. Regression. Regression estimates the relationship among variables. It produces a function based on observed data and then uses it to make predictions. Under the context of resource estimation, the auto-scaler can record system utilization, application performance, and the workload for regression. As more data are available, the predicted results also become more accurate. Although regression requires the user to determine the function type first, for example, whether the relationship is linear or quadratic, in the case of auto-scaling web applications, it is generally safe to assume a linear function.

Chen et al. [Chen et al. 2008] used regression to dynamically build the CPU utilization model of Live Messenger given number of active connections and login rate. The model is then used for resource provision. Bodik et al. [Bi et al. 2010] employed smoothing splines nonlinear regression to predict mean performance under certain amount of resources. Then they calculated the variance based on the estimated mean. After that they used a local polynomial (LOESS) regression to map mean performance to variance. Through this method, they found out that higher workload results in both mean and variance of the response time to increase. To detect sudden changes, they rely on conducting statistical hypothesis testing of the residual distribution in two time frames with probably different sizes. Suppose the testing result is statistically significant, the model needs to be retrained. Padala et al. [Padala et al. 2009] utilized auto-regressive-moving-average (ARMA) to dynamically learn the relationship between resource allocation and application performance considering all resource types in all tiers. Gambi et al. [Gambi et al. 2013] proposed an auto-scaler using a Kriging model. Kriging models are spatial data interpolators akin to radial basis functions. These models extend traditional regression with stochastic Gaussian processes. The major advantage of them is that they can converge quickly using less data samples. Grimaldi et al. [Grimaldi et al. 2015] proposed a Proportional-Integral-Derivative (PID) controller that automatically tunes parameters to minimize integral squared error (ISE) based on a sequential quadratic programming model.

Yanggratoke et al. [Yanggratoke et al. 2015] proposed a hybrid approach of offline learning and online learning. They first used a random forest model and traces from a testbed to train the baseline. Then they applied regression-based online learning to train the model for real-time resource estimation.

8.6. Hybrid Approaches

All the previous listed approaches have their own cons and pros. Therefore, some works have integrated multiple methods together to perform resource estimation. We classify them as hybrid approaches and individually introduce them and their rationales of such integration.

Rule-based systems are inflexible when significant changes occur to applications and often require expert knowledge to design and test. However, if the rules can be constructed dynamically and adaptively by some learning techniques, such concern is vanished. Jing et al [Jing et al. 2007] and Jamshidi et al [Jamshidi et al. 2016] proposed systems that combines machine learning and fuzzy rule-based inference. They utilized machine learning to dynamically construct and adjust the rules in the fuzzy inference engine. Lama and Zhou [Lama and Zhou 2009] first proposed a fixed fuzzy-based system with a self-adaptive component that dynamically tunes the output scaling factor. After that they built another fuzzy inference system as a four layer neural network [Lama and Zhou 2010] in which membership functions and rules can self-evolve as the time passes.

Some analytical queueing models require the observation of volatile metrics that are hard to measure directly and use these metrics and the model to estimate performance. In these cases, a common solution is to use machine learning approaches

to dynamically estimate the concealed metrics. Gandhi et al. [Gandhi et al. 2014a] adopted Kalman filter to assess the average service time, background utilization, and end-to-end network latency. Zhang et al. [Zhang et al. 2007] employed application profiling and regression to learn the relationship of average CPU utilization and average service time at each tier under given request mix in order to solve their queueing network model using Mean Value Analysis.

To mitigate the drawback of machine learning approaches, which are slow to converge and may cause plenty of SLA violations, another model can be used to temporarily substitute the learning model and then shift it back after the learning process has converged. Tesauro et al. [Tesauro et al. 2007] and Gambi et al. [Gambi et al. 2015] proposed this kind of systems. Both of them utilized an analytical queueing model for temporary resource estimation during training period. Tesauro et al. [Tesauro et al. 2007] employed reinforcement learning while Gambi et al. [Gambi et al. 2015] adopted a Kriging-based controller for training.

9. OSCILLATION MITIGATION

Oscillation is the situation that the auto-scaler continuously performs contradictory scaling operations back and forth, such as provisioning 2 VMs and then in short time deprovisioning 2 VMs. It happens when monitoring and scaling operations are too frequent, or the auto-scaler is poorly configured. Such concerns are magnified when dealing with rule-based auto-scalers whose resource estimations are purely empirical and coarse-grained. If the scaling thresholds are poorly configured, oscillation is likely to happen. For example, suppose the scale-up threshold is set to 70%, the scale-down threshold is set to 50%, and the current utilization is 71% with only one instance running, the auto-scaler will add one more instance to the cluster in order to reduce the utilization. The utilization then quickly drops to 35%, which is below the scale-down threshold, thus causing oscillation.

9.1. Cooling Time

One common solution adopted by industries [Amazon 2016] to mitigate oscillation is to coercively wait a fixed minimum amount of time between each scaling operations. The time is set by users and is widely called as the cooling time. It should be set to at least the time taken to acquire, boot up, and configure the VM. Such method is simple but effective to avoid frequent scaling operations. However, setting a long cooling time will also result in more SLA violations as the application cannot be scaled up as quickly as before. Also it cannot handle the situation that the auto-scaler is poorly configured.

Another way of setting the cooling time is to further confine the scaling condition. Suppose the monitoring interval of the auto-scaler is 1 minute, we can achieve a prolonged scaling interval by setting the scaling trigger as how many times the monitored value exceeds the defined threshold consecutively.

9.2. Dynamic Parameters

Besides static cooling time, researchers have proposed approaches that dynamically adjust some parameters in order to reduce the possibility of causing oscillation.

Lim et al. [Lim et al. 2009; Lim et al. 2010] described an approach through dynamically tuning the triggering thresholds for scale-down operations. The core idea is to increase the scale-down threshold when more resources are allocated so as to decrease the target utilization range and vice versa when resources are deallocated. This can effectively mitigate oscillation if the application resource requirement varies significantly during peak time and non-peak time. This is because during non-peak time, a large target range is desirable to avoid the situation described in the poorly config-

ured example, while during peak time, a small target range is preferred to keep the utilization as close to the scale-up threshold as possible.

Bodik et al. [Bodik et al. 2009] introduced a mechanism that they call, “hysteresis parameters”, to reduce oscillation. These parameters control how quickly the controller provisions and deprovisions resources. They are determined by simulations using Pegasus, an algorithm that compares different control settings to search the suitable one. Pralada et al. [Patala et al. 2009] used a stability factor to adjust the aggressiveness of the system. As the factor increases, the control objective will be more affected by the previous allocation. As a result, the system responds more slowly to the resulted errors caused by the previous actions in the following resource scaling windows and thus reduces oscillations. Lama and Zhou [Lama and Zhou 2009] employed a similar approach on their fuzzy-based system. Their system is more advanced and flexible as the factor is self-tunable during runtime according to the resulted errors.

9.3. Theory

The above methods are only capable of mitigating the possibility of oscillations. If in theory we can identify the settings that might cause oscillations and thus pose restriction on such settings, the risk of oscillation will be completely eliminated. Cunha et al. [Cunha et al. 2014] and Netto et al. [Netto et al. 2014] adopted this approach and presented models that identify the potential oscillation conditions in their rule-based systems.

10. SCALING TIMING

When to scale the application is a critical question needed to be answered by auto-scalers. However, there is no perfect answer for that as different applications have diverse workload characteristics, and preference of cost and QoS. Auto-scalers can be classified into two groups based on this criteria: systems that reactively scale the application only when necessary according to the current status of the application and the workload, and systems that support proactively provision or deprovision resources considering the future needs of the application.

For applications with gradual and smooth workload changes, reactive systems are usually preferred because they can save more resources without causing significant amount of SLA violations. In contrast, applications with drastic workload changes or strict SLA requirements often require proactive scaling before the workload actually increases to avoid incurring large amount of SLA violations during provisioning time. Such strategy relies on prediction techniques to timely foresee incoming workload changes. Prediction is the process of learning relevant knowledge from the past history and then apply this knowledge to foresee the future behaviours of some object. The assumption that behaviours are predictable lies that they are not completely random and follow some rules. Therefore, workload prediction is only viable for workload with patterns and thus, cannot handle random burst of requests, which is common in some applications, like news feed and social network. For these bursty workload scenarios, currently there is no effective solution and we can only deal with them reactively in the best effort. Hence, regardless existence of support for proactive scaling, a qualified auto-scaler should always be able to scale reactively.

10.1. Proactive Scaling

As the accuracy of the prediction algorithm determines the capability of the auto-scaler to proactively scale applications, in this section, we survey prediction algorithms that have been employed by state-of-the-art works.

10.1.1. Workload Prediction Data Source. To predict the workload, it is necessary to study the past workload history to understand workload characteristics, including the workload intensity and workload mix during each time frame. General purpose workload predictors usually only utilize past workload information to make predictions.

Besides workload history, individual applications can rely on available information from other aspects to predict request bursts that are impossible to be derived from past workload data alone, such as weather information for an outdoor application, and political events for a news feed application. However, the relevant parameters are application specific and thus this feature is very difficult to be integrated into a general purpose auto-scaler. In addition, it is also challenging to devise a prediction algorithm with real-time accuracy for resource provisioning, because there are too many parameters in the model and errors can easily accumulate. The work by Frey et al. [Frey et al. 2014] considers multiple outside parameters in an auto-scaler. Their approach integrates all the prediction information into a fuzzy controller.

Though it is difficult to predict the right amount of workload with outside information, it is viable to timely detect events that may affect incoming workload intensity through social media and other channels [You et al. 2013]. Since this is a broad topic itself, we focus on prediction algorithms based on workload history.

10.1.2. Prediction Horizon and Control. Typically, a prediction algorithm loops in a certain interval in order to predict the average or maximum workloads arriving to the application during each of the next few intervals, which form the prediction horizon. The prediction horizon determines how far in the future the system aims to predict.

To use the prediction results in the control part of the auto-scaler, there are generally two popular approaches. The first way, which is adopted by majority of works, adopts the prediction horizon as the control interval and scales the application only based on the predicted workload of the next horizon. The other strategy is called Model Predictive Control (MPC). It sets the control interval the same to the prediction interval. When making decisions, it considers all the intervals within the horizon and determines the scaling operations at each interval using optimization. However, when executing the scaling operations, it only performs the action for the next interval and discards the operations for the rest intervals in the horizon. This method mitigates the problem of provision for short-term benefits, but it requires solving complex optimization models, and thus, consumes much more computing power. Ghanbari et al. [Ghanbari et al. 2012; Ghanbari et al. 2014], and Zhang et al. [Zhang et al. 2013] employed this approach.

To tune the length of horizon, we can either adjust the length of each interval or the number of intervals in the horizon. The size of the interval is critical to prediction accuracy. Large interval can significantly degrade the prediction accuracy and is useless for real-time control if the interval is larger than the control interval of the auto-scaler. The number of intervals in the horizon is also a very important parameter, especially for the MPC approach. A balanced number should be chosen for the auto-scaler to reach good performance. If it is too small, MPC cannot fully realize its potential to make decisions for the long-term benefit. While a large number may mislead the auto-scaler as the predictions for the intervals far in the future become more and more inaccurate.

10.1.3. Workload Prediction Algorithms. In terms of workload prediction algorithms, they can be coarsely classified into two types: prediction according to recent trends and prediction based on regular patterns.

Prediction according to recent trends aims to use the workload data monitored in the near past to determine whether the workload is increasing or decreasing and how much it will change. In this case, only a few data is stored for prediction purpose.

Mature time series analysis algorithms are commonly applied to this type of prediction tasks, such as linear regression [Bodk et al. 2009], various autoregressive models (AR) [Chen et al. 2008; Roy et al. 2011; Fang et al. 2012; Yazdanov and Fetzer 2013; Yang et al. 2014], and neural network-based approaches [Prodan and Nae 2009; Aniello et al. 2014; Nikraves et al. 2015]. Besides using time-series analysis, Nguyen et al. [Nguyen et al. 2013] proposed another method, which considers each time interval as a wavelet-based signal and then applies signal prediction techniques.

Prediction algorithms based on regular patterns assume the workload is periodic, which is valid for many applications as they tend to be more accessed during day-time, week days, or certain days in a year (tax report period, Christmas holidays). By finding these patterns, predictions then can be easily made. Different from prediction algorithms based on recent trends, this type of algorithm requires a large workload archive across long period of time. To identify patterns, various approaches have been explored when building auto-scalers. Fang et al. [Fang et al. 2012] employed signal processing techniques to discover the lowest dominating frequency — the longest repeating pattern. Silva Dias et al. [da Silva Dias et al. 2014] utilized Holt-Winter model, which aims to identify the characteristics of the seasonality in the workload for prediction. Jiang et al. [Jiang et al. 2013] devised an approach by first identifying the top K most relevant monitored data using an auto-correlation function and then employing linear regression on the selected data for prediction. Urgaonkar et al. [Urgaonkar et al. 2008] adopted an algorithm based on histogram for workload with daily patterns.

Herbst et al. [Herbst et al. 2014] integrated many predictors into one system. They presented an approach to dynamically select appropriate prediction methods according to the extracted workload intensity behaviour (WIB, simply the workload characteristics) and user's objectives. The mappings of predication methods to WIBs are stored in a decision tree and are updated during runtime based on the recent accuracy of each algorithm.

10.1.4. Resource Usage Prediction. Instead of predicting workload, it is also possible to directly predict resulted resource usage according to the historic usage data. This strategy is commonly used by auto-scalers only support vertical scaling, as for a single machine, resource usage can substitute workload intensity. Some systems [Islam et al. 2010; Caron et al. 2011; Almeida Morais et al. 2013] that target horizontal scaling also follow this strategy to together accomplish both workload prediction and resource estimation.

Gong et al. [Gong et al. 2010] used singal processing to discover the logest repeating pattern of resource usage and then relied on dynamic time warping (DTW) algorithm to do the prediction. For applications without repeating patterns, they referred to a discrete-time Markov chain with finite states to derive a near prediction of future values. Islam et al. [Islam et al. 2010] explored using linear regression and neural network to predict CPU usage. Caron et al. [Caron et al. 2011] adopted a pattern matching approach which abstracts it as a string matching problem and solved it using the Knuth-Morris-Pratt (KMP) algorithm. Yazdanov et al. [Yazdanov and Fetzer 2012] utilized an auto-regressive (AR) method to predict short-term CPU usage. AlmeidaMorais et al. [Almeida Morais et al. 2013] employed multiple time series algorithms to predict CPU usage, and based on their runtime accuracy, the best is selected. Loff and Garcia [Loff and Garcia 2014] also used multiple prediction algorithms. However, instead of selecting the best one, their system combine the results of different predictors using weighted k-Nearest Neighbours algorithm. The weight of each predictor is dynamically adjusted according to their recent accuracy.

11. SCALING METHODS

Depending on the specific cloud environment, elastic scaling can be performed vertically, horizontally, or both. Each of them has their own advantages and limitations. In this section, we discuss the key factors that need to be considered when making the provisioning plan.

11.1. Vertical Scaling — VM Resizing

Vertical scaling means removing or adding resources, including CPU, memory, I/O, and network, to or from existing VMs. To dynamically perform these operations, modern hypervisors utilize mechanisms such as CPU sharing and memory ballooning, to support CPU and memory hot-plug. However, major cloud providers, such as Amazon, Google, and Microsoft, do not support adjusting resources during runtime. In these platforms, it is essential to shut down the instance first in order to add resources. Some providers like Centurylink¹ allow users to vertically scale CPU cores without downtime. Profitbricks² permits to add both CPU and memory to the VMs dynamically.

Vertical scaling is considered not suitable for highly scalable applications due to its limitations. Ideally, the maximum capacity a VM is able to scale to is the capacity of the physical host. However, usually there are multiple VMs residing on the same physical machine competing for resources, which further confines the potential scaling capability. Though limited, dynamic vertical scaling outperforms horizontal scaling in provision time as it can be in effect instantaneously. Besides, some services or components that are difficult to replicate during runtime, such as database server, and stateful application server, can be benefited by vertical scaling. Dawoud et al. [Dawoud et al. 2012] conducted a experimental study of vertical scaling using RUBBOS benchmark on both its application server and database, which highlights the above mentioned advantages of vertical scaling.

Many auto-scalers have been developed using solely vertical scaling to manage VMs on the same physical host. Some of them only considered scaling CPU resources [Kalyvianaki et al. 2009; Shen et al. 2011; Yazdanov and Fetzer 2012; Spinner et al. 2014]. Some targeted both CPU and memory [Gong et al. 2010; Zhu and Agrawal 2012; Dawoud et al. 2012; Yazdanov and Fetzer 2013]. Jing et al. [Jing et al. 2007] focused on CPU in the prototype and claimed their method can be extended to other resources. Bu et al. [Bu et al. 2013] proposed a system that not only adjusts CPU and memory allocation, but also application parameters. Padala et al. [Padala et al. 2009] scaled both CPU and disk. These systems are mostly deployed in private clouds or by cloud providers.

11.2. Horizontal Scaling — Launching New VMs

Horizontal scaling is the core of the elasticity feature of the cloud. Most cloud providers offer standardized VMs of various sizes for customers to choose. Others allow users to customize their VMs with specific amount of cores, memory, and network bandwidth. Besides, there are multiple pricing models co-existing in the current cloud market, which further increases the complexity of the provision problem.

11.2.1. Heterogeneity. Regarding a single tier/service within a web application, if the billing is constant, the use of homogeneous VMs is well acceptable as it is easy to manage. Actually, the auto-scaling services offered by cloud providers only allow the use of homogeneous VMs. Selecting which type of VM is considered the responsibility of users

¹<https://www.clt.io/autoscale/>

²<https://www.profitbricks.com/help/Live-Vertical-Scaling>

in commercial auto-scaling systems. The optimal solution depends on the resource profile of the tier/service, e.g., whether it is CPU intensive or memory intensive, and the workload characteristic. If the workload is always large enough, then small and large instances make little difference. While for small and fluctant workload, smaller instances are preferred as scaling can be conducted in finer granularity and thus save more cost.

Cost-efficiency of VM is highly co-related to the application and workload. If changes happen to them, the choice of VM type should also be reconfigured. Grozev and Buyya [Grozev and Buyya 2016] proposed a method that detects changes online using the Hierarchical Temporal Memory (HTM) model and a dynamically trained artificial neural network (ANN), and then reselects the most cost-efficient VM type.

The use of heterogeneous VMs to scale web applications has been explored in the literature. Under conventional billing where price grows linearly with VM's capability, heterogeneity can bring some extra cost-saving but not significant. Furthermore, it is often computing-intensive to search the provision plan with combination of heterogeneous VMs. Srirama and Ostovar [Srirama and Ostovar 2014] employed linear programming to solve the provision problem, yet only achieved limited cost saving against AWS auto-scaling. Fernandez et al. [Fernandez et al. 2014] abstracted the provision combinations as a tree and searched the suitable provision by traversing the tree according to different SLAs. In a different scenario in which the capability of VMs increases exponentially to their prices, heterogeneity has the potential to save significant cost, which is shown in Sedaghat et al.'s work [Sedaghat et al. 2013] and Upendra et al.'s work [Upendra et al. 2011]. They employed a similar approach by considering the transition cost (the time and money spent to convert from the current provision to the target provision) and the cost of resource combination in the optimization problem.

We proposed an auto-scaling system [Qu et al. 2016] that uses heterogeneous spot instances to provision web applications. The intention of using heterogeneous VMs in this case is to boost the reliability of spot backed clusters to save cost, which is explained in the following section.

11.2.2. Pricing Models. The current cloud pricing models can be classified into three types by pricing model: on demand, reserved, and rebated. In on demand mode, the provider sets a fixed unit price for each type of VM or unit of certain resource, and charges the user by units of consumption. Users are guaranteed to obtain the requested resources and agreed performance. This is the mode most auto-scalers assume the target application is adopting. The reserved mode requires the user to pay an upfront fee for cheaper use of certain amount of resources. If highly utilized, users can save considerable amount of money than acquiring resources in on demand mode. Providers create the rebate mode aiming to sell their spare capacity. Usually they are significantly cheaper than on demand resources. There are several ways to offer rebated resources. Amazon employed an auction mechanism to sell instances, called spot instances. User are required to submit a bid on the resources. Suppose the bid exceeds the current market price, the bid is fulfilled and the user is only charged by the current market price. The acquired spot instances are guaranteed to have the same performance of their on demand counterparts. However, they are reclaimed whenever the market price goes beyond user's bidding price. Google offer their spare capacity as preemptible VMs. Different from Amazon, they set a fixed price to the VM, which is 30% of the regular price, and the VM is available at most for 24 hours. Reabted instances are considered not suitable to host web applications that are availability-critical. Clus-

terK³, and our previous work [Qu et al. 2016] however have demonstrated that it is feasible to build an auto-scaling system utilizing spot instances by exploiting diverse market behaviours of various spot markets in order to achieve both high availability and considerable cost saving.

Also pricing models can be classified according to billing period, which is the minimum unit consumption. Providers have set their billing period to every minute, hour, day, week, month, or year. The length of the billing period has a significant impact on the cost-efficiency for elasticity. Obviously, the shorter the billing period, the more flexible and cost-efficient it is for auto-scaling. If the billing period exceeds the order of hour, there is no use in applying auto-scaling, since provisioning for the peak load of the day incurs the same cost.

11.3. Hybrid

As mentioned, horizontal scaling is slow in provision and vertical scaling is confined by the resources available in the host. To mitigate these issues, it is natural to employ vertical scaling and horizontal scaling together. The idea is to utilize vertical scaling when possible to quickly adapt to changes and only conduct horizontal scaling when vertical scaling reaches its limit. Urgaonkar et al. [Urgaonkar et al. 2008], Huber et al. [Huber et al. 2011], Rui et al. [Rui et al. 2012], and Yang et al. [Yang et al. 2014] followed this strategy.

Mixing vertical scaling and horizontal scaling can also bring cost benefit. Dutta et al. [Dutta et al. 2012], and Gandhi et al. [Gandhi et al. 2014b] explored optimization techniques to search for the scaling plan that incurs the least cost with hybrid of vertical and horizontal scaling.

Vertical scaling and horizontal scaling can be separately applied to different components of the application as well since some parts such as database servers are difficult to be horizontally scaled. Nisar et al. [Nisar et al.] demonstrated this approach in a case study.

12. ENVIRONMENT

12.1. Single Cloud

The auto-scaling challenges and developments in single cloud environment have been thoroughly covered in the previous sections. To summarize the findings, based on the taxonomy and explanation of the concepts, we list the characteristics of the surveyed works in Table I.

12.2. Multiple Clouds

The modern applications are often deployed in multiple cloud data centers for various purposes [Grozev and Buyya 2014a]: 1) multi-cloud deployment helps reducing response latency if users can be served by the nearby data center; 2) it improves availability and reliability of the application against data center outages by replicating the application stack in multiple regions; 3) it enables the service provider to exploit the cost differences among different vendors; and 4) it prevents vendor lock-in. Auto-scaling systems should be able to support this type of deployment as well.

³<http://www.geekwire.com/2015/amazon-buys-clusterk-a-startup-that-lets-developers-run-aws-workloads-more-cheaply/> acquired by AWS in 2015

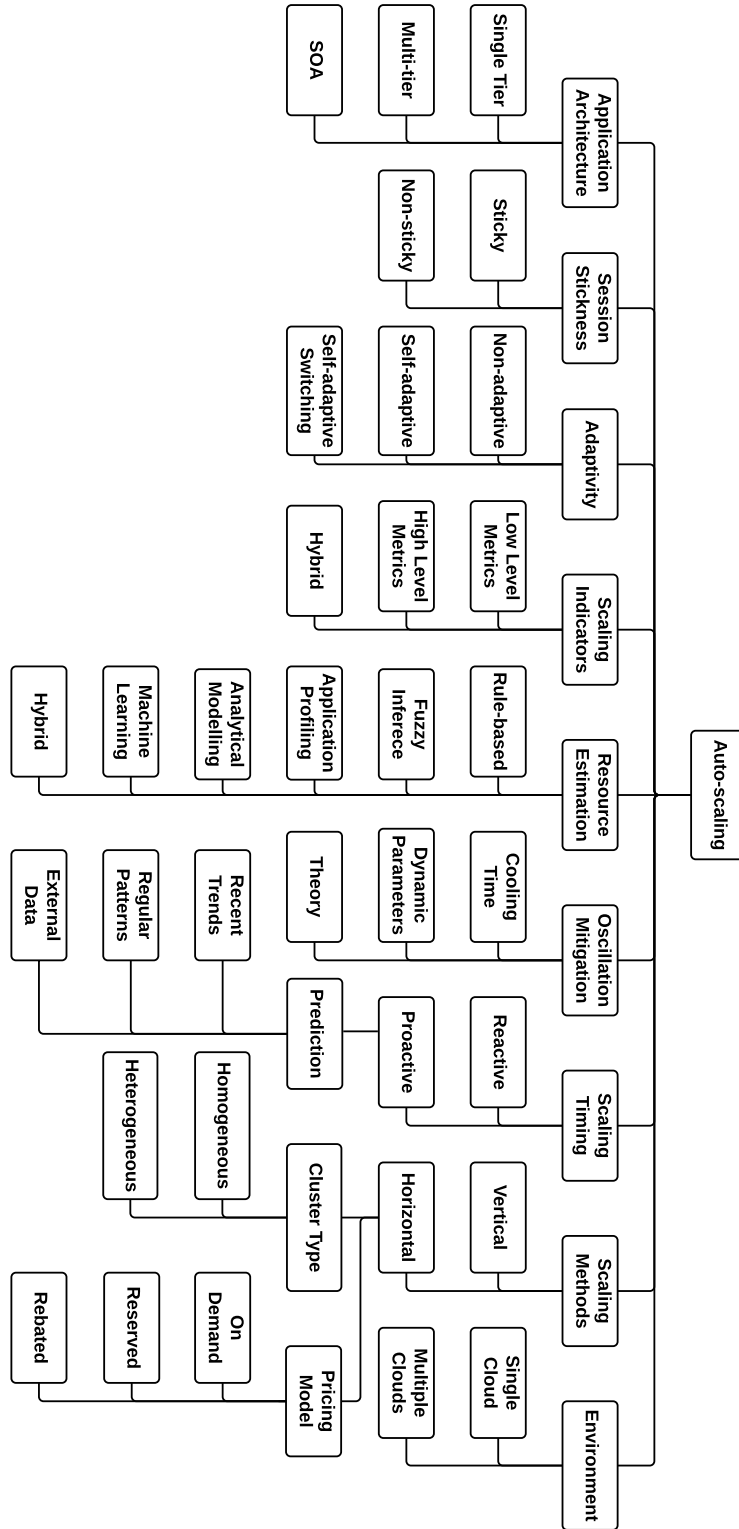


Fig. 3: The taxonomy for auto-scaling web applications in clouds

Table I: A Review of auto-scaling properties of key works for single cloud

Work	Application Architecture	Sticky Session	Adaptivity	Scaling Indicators	Resource Estimation	Oscillation Mitigation	Proactive	Scaling Methods
[Doyle et al. 2003]	single-tier	✓	non-adaptive	hybrid	analytical model	—	✗	vertical
[Kamra et al. 2004]	3-tier	✓	self-adaptive	high level	analytical model	—	✗	vertical
[Tesauro 2005]	single-tier	✗	self-adaptive	high level	reinforcement learning	—	✗	hom. horizontal
[Tesauro et al. 2007]	single-tier	✗	self-adaptive	high level	hybrid	—	✗	hom. horizontal
[Jing et al. 2007]	single-tier	✓	self-adaptive	high level	hybrid	—	✗	vertical
[Villela et al. 2007]	single-tier	✗	non-adaptive	hybrid	analytical model	—	✗	hom. horizontal
[Zhang et al. 2007]	multi-tier	—	—	hybrid	hybrid	—	—	—
[Chen et al. 2008]	single-tier	✓	self-adaptive	hybrid	regression	—	✓	hom. horizontal
[Urgaonkar et al. 2008]	multi-tier	✗	non-adaptive	high level	analytical model	—	✓	hybrid
[Iqbal et al. 2009]	single-tier	✗	non-adaptive	high level	rule-based	—	✗	hetr. horizontal
[Lim et al. 2009]	single-tier	✗	self-adaptive	low level	rule-based	dynamic para.	✗	hom. horizontal
[Bodk et al. 2009]	single-tier	✗	self-adaptive	high level	regression	dynamic para.	✓	hom. horizontal
[Padala et al. 2009]	multi-tier	✓	self-adaptive	hybrid	regression	dynamic para.	✗	vertical
[Kalyvianaki et al. 2009]	single-tier	✓	self-adaptive	low level	rule-based	—	✗	vertical
[Lama and Zhou 2009]	multi-tier	✗	self-adaptive	high level	fuzzy inference	dynamic para.	✗	hom. horizontal
[Lim et al. 2010]	storage-tier	✗	self-adaptive	low level	rule-based	dynamic para.	✗	hom. horizontal
[Dutreilh et al. 2010]	single-tier	✗	self-adaptive	high level	hybrid	cooling time	✗	hom. horizontal
[Gong et al. 2010]	single-tier	✓	self-adaptive	low level	hybrid	—	✓	vertical
[Islam et al. 2010]	single-tier	✗	self-adaptive	low level	neural net./regression	—	✓	—
[Lama and Zhou 2010]	multi-tier	✗	self-adaptive	high level	hybrid	—	✗	hom. horizontal
[Bi et al. 2010]	multi-tier	✗	non-adaptive	high level	analytical model	—	✗	hom. horizontal
[Singh et al. 2010]	multi-tier	✗	non-adaptive	high level	analytical model	—	✗	hom. horizontal
[Jiang et al. 2010]	SOA	✗	self-adaptive	high level	analytical model	—	✗	hom. horizontal
[Chieu et al. 2011]	single-tier	✓	non-adaptive	high level	rule-based	—	✗	hom. horizontal
[Dutreilh et al. 2011]	single-tier	✗	self-adaptive	high level	reinforcement learning	—	✗	hom. horizontal
[Li and Venugopal 2011]	single-tier	✗	self-adaptive	low level	reinforcement learning	—	✗	hom. horizontal
[Caron et al. 2011]	single-tier	✗	self-adaptive	low level	string matching	—	✓	—
[Huber et al. 2011]	single-tier	✗	non-adaptive	hybrid	rule-based	—	✗	hybrid
[Iqbal et al. 2011]	multi-tier	✗	self-adaptive	hybrid	hybrid	—	✗	hom. horizontal
[Jiang et al. 2011]	multi-tier	✗	non-adaptive	hybrid	online profiling	—	✗	hetr. horizontal
[Malkowski et al. 2011]	multi-tier	✗	self-adaptive	hybrid	hybrid	—	✗	hom. horizontal
[Roy et al. 2011]	multi-tier	✗	non-adaptive	hybrid	analytical model	—	✓	hom. horizontal
[Upendra et al. 2011]	multi-tier	✗	non-adaptive	high level	profiling	—	✓	hetr. horizontal
[Vasić et al. 2012]	single-tier	✗	self-adaptive	low level	online profiling	—	✗	hom. horizontal
[Ali-Eldin et al. 2012]	single-tier	✗	self-adaptive	high level	analytical model	—	✓	hom. horizontal
[Dawoud et al. 2012]	single-tier	✗	non-adaptive	low level	rule-based	—	✗	compare ver. hor.

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Table I – continued from previous page

Work	Application Architecture	Sticky Session	Adaptivity	Scaling Indicators	Resource Estimation	Oscillation Mitigation	Proactive	Scaling Methods
[Fang et al. 2012]	single-tier	×	—	—	—	—	✓	—
[Yazdanov and Fetzer 2012]	single-tier	✓	self-adaptive	low level	regression	—	✓	vertical
[Ghanbari et al. 2012]	single-tier	×	non-adaptive	high level	analytical model	—	×	hetr. horizontal
[Zhu and Agrawal 2012]	single-tier	✓	self-adaptive	low level	reinforcement learning	—	×	vertical
[Dutta et al. 2012]	multi-tier	×	non-adaptive	hybrid	application profiling	—	×	hybrid
[Gandhi et al. 2012]	multi-tier	×	non-adaptive	hybrid	profiling	—	×	hom. horizontal
[Rui et al. 2012]	multi-tier	×	non-adaptive	high level	rule-based	—	×	hybrid
[Jiang et al. 2013]	single-tier	×	non-adaptive	high level	analytical model	—	✓	hom. horizontal
[Al-Haidari et al. 2013]	single-tier	×	non-adaptive	high level	rule-based	—	×	hom. horizontal
[Bu et al. 2013]	single-tier	✓	self-adaptive	high level	reinforcement learning	—	×	vertical
[Gambi et al. 2013]	single-tier	×	self-adaptive	low level	Kriging regression	—	×	hom. horizontal
[Barrett et al. 2013]	single-tier	×	self-adaptive	high level	reinforcement learning	—	×	hetr. horizontal
[Sedaghat et al. 2013]	single-tier	×	non-adaptive	high level	—	—	×	hetr. horizontal
[Yazdanov and Fetzer 2013]	single-tier	×	self-adaptive	hybrid	reinforcement learning	—	✓	vertical
[Ali-Eldin et al. 2013]	single-tier	×	switch	—	—	—	✓	hom. horizontal
[Almeida Morais et al. 2013]	single-tier	×	self-adaptive	low level	various regressions	—	✓	hom. horizontal
[Nguyen et al. 2013]	multi-tier	×	non-adaptive	hybrid	online profiling	—	✓	hom. horizontal
[Herbst et al. 2014]	—	×	self-adaptive	—	—	—	✓	—
[Grozev and Buyya 2014b]	single-tier	✓	non-adaptive	low level	rule-based	—	×	hom. horizontal
[da Silva Dias et al. 2014]	single-tier	×	non-adaptive	hybrid	rule-based	—	✓	hom. horizontal
[Loff and Garcia 2014]	single-tier	×	non-adaptive	low level	rule-based	—	✓	hom. horizontal
[Cunha et al. 2014]	single-tier	×	self-adaptive	low level	rule-based	theory	×	hom. horizontal
[Netto et al. 2014]	single-tier	×	self-adaptive	low level	rule-based	theory	×	hom. horizontal
[Aniello et al. 2014]	single-tier	×	non-adaptive	high level	analytical model	—	✓	hom. horizontal
[Frey et al. 2014]	single-tier	×	non-adaptive	hybrid	fuzzy inference	—	✓	hom. horizontal
[Yang et al. 2014]	single-tier	×	non-adaptive	hybrid	rule-based	—	✓	hetr. horizontal
[Fernandez et al. 2014]	single-tier	×	non-adaptive	high level	profiling	—	×	hetr. horizontal
[Srirama and Ostovar 2014]	single-tier	×	non-adaptive	—	—	—	×	hetr. horizontal
[Gandhi et al. 2014b]	single-tier	×	self-adaptive	high level	analytical model	—	×	hybrid
[Spinner et al. 2014]	single-tier	✓	self-adaptive	hybrid	analytical model	—	×	vertical
[Gergin et al. 2014]	multi-tier	×	non-adaptive	high level	analytical model	—	×	hom. horizontal
[Han et al. 2014]	multi-tier	×	non-adaptive	high level	analytical model	—	×	hom. horizontal
[Kaur and Chana 2014]	multi-tier	×	non-adaptive	high level	analytical model	—	✓	hom. horizontal
[Gandhi et al. 2014a]	multi-tier	×	self-adaptive	hybrid	analytical model	—	×	hom. horizontal
[Nikraves et al. 2015]	—	—	—	—	—	—	✓	—
[Yanggratoke et al. 2015]	single-tier	×	self-adaptive	high level	batch & online learning	—	×	hom. horizontal
[Grimaldi et al. 2015]	single-tier	×	self-adaptive	low level	rule-based	—	×	hom. horizontal

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Table I – continued from previous page

Work	Application Architecture	Sticky Session	Adaptivity	Scaling Indicators	Resource Estimation	Oscillation Mitigation	Proactive	Scaling Methods
[Gambi et al. 2015]	single-tier	×	self-adaptive	high level	hybrid	—	×	hom. horizontal
[Salah et al. 2015]	single-tier	×	non-adaptive	high level	analytical model	—	×	hom. horizontal
[Iqbal et al. 2015]	multi-tier	×	self-adaptive	high level	reinforcement learning	—	×	hom. horizontal
[Amazon 2016]	single-tier	×	non-adaptive	high/low	rule-based	cooling time	×	hom. horizontal
[RightScale 2016]	single-tier	×	non-adaptive	high/low	rule-based	cooling time	×	hom. horizontal
[Qu et al. 2016]	single-tier	×	non-adaptive	low level	profiling	—	×	hetr. horizontal
[Jamshidi et al. 2016]	single-tier	×	self-adaptive	high level	hybrid	—	×	hom. horizontal
[Grozev and Buyya 2016]	single-tier	×	self-adaptive	hybrid	rule-based	—	×	hetr. horizontal

When expanded to multiple clouds, auto-scaling remains the same problem if applications in different cloud data centers are managed completely standalone, which is the common practice of the industry. In this case, usually the service provider firstly selects a set of cloud data centers to host the application. Each data center is intended to only serve requests coming from nearby users and is separately managed by a dedicated local auto-scaler without global coordination of request routing and resource provision.

Though easy to manage, such strategy is not optimal in an environment that both workload and resource price are highly dynamic. As time passes, it is better to move resources to cheaper data centers in order to save cost, or to data centers that are more close to certain groups of users so as to improve their QoS. Auto-scaling becomes more complicated in these scenarios as the system not only needs to make decisions on resource provision, but also location selection and request routing.

Some works explored holistic solutions for resource management of web applications in multiple clouds. They can be further divided into two types. The first type always deploys the whole application stacks in the chosen data centers. The other type allows separate deployment of application components in different data centers.

Zhang et al. [Zhang et al. 2013] and Rodolakis et al. [Rodolakis et al. 2006] targeted the first type of problems. Zhang et al. [Zhang et al. 2013] assumed that each potential data center is capacitated and applications are deployed in one VM. Their objective is to minimize the total cost of resources used by the application through dynamically acquiring and releasing servers from geographically dispersed data centers under the constraint of demand, capacity, and SLA. They employed the Model Predictive Control (MPC) framework and a quadratic optimization model to adjust resource allocation in each data center and request routing from each location. While Rodolakis et al. [Rodolakis et al. 2006] considered a scenario that without data center capacity constraints and dynamic pricing. They dissected the problem into three parts and proposed approximation algorithms for each of them to form an integrated solution. Calcavecchia et al. [Calcavecchia et al. 2012] devised a decentralized auto-scaling system for multiple clouds. It is able to autonomously start VMs at hot place by voting of adjacent VMs and balance the load among them.

Regarding the second problem type, Tortonesi and Foschini [Tortonesi and Foschini 2016] proposed a genetic-based algorithm to search the deployment of a two-tier applications across multiple clouds with minimum resource and SLA violation cost. Rochman [Rochman et al. 2014] modeled the problem as a min-cost flow problem and solved it with Bipartite Graph Algorithm. Grabarnik et al. [Grabarnik et al. 2014] added more complexity to the problem by also optimizing the chosen VM types for each tier in a multi-tier application. They devised a 2-phase metaheuristic algorithm with the outer phase responsible for assigning components to data centers also using a genetic-based algorithm, and the inner phase using a random search algorithm to map the components to specific types of VMs. None of these solutions bears reliability in mind, which is important for this type of deployment. If poorly planned, instead of improving reliability and availability of the application, dispersing replicas into multiple data centers can create multiple points of failures and greatly reduce uptime. It is important for the auto-scaler to ensure that every component is properly replicated in multiple data centers all the time.

Cost of data replication is another reason that makes it beneficial to provide a holistic solution for auto-scaling in multiple clouds for some applications, such as video streaming applications. For these applications, they need to ensure QoS by ensuring there are enough bandwidth between the video storage site and the end customer. The simplest way is to replicate all the videos in every data center and serve customers from the corresponding nearest one with ample bandwidth. However, it is unrealistic

and extremely wasteful. To save cost, the service provider needs to decide for each video how many replicas it should keep and where they should be placed. Along with the data, serving applications should be co-located as well and user requests need to be properly diverted to specific serving replicas because of the bandwidth limit of serving VMs. To realize the above targets, Wu et al. [Wu et al. 2012] proposed and implemented a prototype using Model Predictive Control and subgradient algorithm.

The mentioned holistic approaches require solving complex optimization problems, which takes considerable time. This makes them only applicable to perform auto-scaling in coarse-grained time intervals and thus limits their ability to react to drastic workload changes. Therefore, for applications with highly variable workload, the choice of using holistic approaches is doubtful. To compensate this shortcoming, local auto-scalers can be deployed in each data center to handle the fine-grained scaling needs.

13. DISCUSSION AND FUTURE DIRECTIONS

According to the taxonomy and analysis, it is apparent that there still are gaps between the current solutions and the ideal auto-scaler in various aspects. In the following section, we discuss them and point out potential methods and directions to improve the current solutions.

13.1. SOA

The research on scaling complex service-oriented applications are still at early stage and limited literature can be found in this area. Moreover, due to lack of accurate resource estimation models, only a simple approach that tentatively and recursively provision resources to a selected service is proposed, which takes a long time to reach the target overall performance. If accurate resource estimation model is available for SOA applications, the auto-scaler can provision resources in one shot to every service with minimum provision time. Models using queueing networks can be explored to fulfill the gap. To minimize cost, it also calls for efficient online optimization algorithms to decide how each service should be provisioned in real-time.

13.2. Monitoring Tools for Hidden Parameters

To facilitate accurate resource estimation and provision, it is important to implement low cost monitoring tools that can provide real-time measurement about hidden parameters, such as average service time, and request mix, for general purpose applications. Because of the intrusive nature of these parameters, such tools can be integrated into application service containers.

13.3. Resource Estimation Models

Although plenty resource estimation models have been proposed for various types of application architectures, they still need to be improved in accuracy, generality, computing requirements, and easiness of use. We believe hybrid estimation models that encompass strengths of both analytical modelling and machine learning approaches are the most promising ones. Other directions, such as general purpose queueing network models for SOA applications and efficient and accurate online profiling techniques, are important and need to be further investigated.

13.4. Provision using Rebated Pricing Models

Besides Amazon's spot cloud, providers like Google and Microsoft have introduced their own rebated pricing models. However, researches have only concentrated on exploring how to utilize Amazon's spot market while have been oblivious to other providers offerings. New works can aim to use cost models from other providers to pro-

vision resources. It is also interesting to research using rebated resources in a multiple cloud environment with resources from multiple data centers of the same provider or from multiple providers to minimize cost under QoS constraints. Besides, the proposed systems only combine on demand resources with rebated resources. Systems that can employ on demand, reserved, and rebated resources would be useful in industry, which can be another potential future research direction.

13.5. Better Vertical Scaling Support

Only a few providers enable users to lively vertical scale their VMs. More researches need to be conducted to ease providers to enable vertical scaling option in their infrastructure. This involves proposing vertical-scaling-aware VM allocation and live migration algorithms, devising and implementing generic vertical scaling APIs, and enhancing support for vertical scaling in hypervisors and operating systems.

13.6. Event-based Workload Prediction

As mentioned before, existing auto-scalers mostly rely on past workload history to predict future workload. With the growing popularity of social media and other real-time information channels, it is interesting to investigate the use of these sources of information to accurately predict workload burst. Although it is difficult to design a general-purpose predictor of this kind for various applications, there is potential to build systems that cater the characteristics of a certain type of applications that can benefit from this approach, such as news applications whose workloads are boosted by events in the physical world, and outdoor applications whose workloads are subject to weather conditions.

13.7. Reliability-aware Multi-cloud Auto-scaling

The holistic auto-scaling solutions in multi-cloud environment ignore the impact on application availability caused by data center outages. It is necessary to address this issue before holistic approaches can be applied in real systems. This requires new models that quantitatively measure the level of reliability for specific deployments and include reliability requirement as a constraint in the optimization problem.

13.8. Energy and Carbon-aware Auto-scaling

The existing works only focus on financial cost and QoS aspects. As another major concern of the ICT sector, energy and carbon footprint should also be considered in the auto-scaling systems. Nowadays, many data centers have been equipped with on-site generators utilizing renewable energy. However, these sources of energy, such as wind and solar, are unstable. To maximize use of on-site renewable energy, auto-scalers can preferentially provision resources in data centers that have renewable energy available. Within a single data center, auto-scalers can utilize vertical scaling as much as possible to avoid starting new physical machines to save energy.

13.9. Container-based Systems

The emergence of containers, especially container supported microservices and service pods, has raised a new revolution in web application resource management. However, dedicated auto-scaling solutions that cater for specific characteristics of the container era are still left to be explored. Though this survey focuses on auto-scalers based on VMs, we believe some of the notions and techniques mentioned in this paper can inspire research of container-based systems as the core requirements of them are similar. However, in some aspects they are different, e.g., containers are more flexible in sizes and quicker and more lightweight to provision. In addition, container-based auto-

scaling problem is also mixed with resource allocation problem as containers need to be scheduled on physical hosts or VMs and consolidated to actually save cost.

14. SUMMARY AND CONCLUSIONS

Auto-scaling is a technique that automatically adjusts the resources provisioned to the applications according to real-time workloads. It helps application providers minimize their resource bills of using cloud resources while meeting QoS expectations of their customers. However, designing and implementing an auto-scaler faces many challenges. Many researches have targeted this problem and various systems with diverse characteristics have been proposed.

In this paper, we surveyed the developments of auto-scaling techniques for web applications in clouds. Auto-scaling systems can be abstracted as a MAPE (Monitoring, Analysis, Planning, and Execution) loop. We identified key challenges need to be addressed in each phase of the loop and presented a taxonomy of auto-scaling systems regarding their key properties. Our taxonomy comprehensively covers the listed challenges and categorizes the works based on their solutions to each challenge. According to the taxonomy, we analyzed the existing techniques in detail to discuss their strength and weakness. Based on the analysis, we proposed some promising directions that the research community can pursue in the future.

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